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ORIGINAL ARTICLE

Artificial intelligence's effect on customer loyalty in the context of electronic commerce

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Abstract
Customer loyalty has been at the heart of business strategic decision-making because of its inherent ability to influence sales. Artificial intelligence, whose recent surge has permeated different aspects of business, has been applied in improving customer loyalty in the ecommerce sector. This study is an investigation into the influence of artificial intelligence on consumer loyalty within the ecommerce industry. We considered ten papers from a host of 345 studies from MDPI, IEEE Xplore, and ABI/INFORM. They were journal articles, white papers, or conference papers. The research process involved several steps, including keyword planning, establishing the inclusion and exclusion criteria, reference checking, expert consultation, documentation of search strategy, coding, and computing the effect sizes. The meta-analysis revealed a strong positive correlation ($r = 0.761$), indicating that AI significantly enhances customer loyalty in e-commerce. This level of correlation implies that AI adoption is strongly associated with customer retention, engagement, and satisfaction in practice. The study concludes that ecommerce platforms adopting artificial intelligence retain their customer bases more effectively than those that do not. For this reason, the study recommends that ecommerce companies should adopt AI technologies, recruit multi-talented AI experts to refine the systems, and invest in research into improving the systems. While the study tried to be comprehensive, the researcher recommends that future studies should consider bigger sample sizes of articles for a more reliable outcome. Additionally, future studies should explore AI's differential impact across e-commerce sectors and customer types to refine strategic implementations.

Keywords Artificial intelligence · Machine learning · Natural language processing · Regression · Customer loyalty · Customer satisfaction · E-commerce

1 Introduction

Artificial Intelligence (AI) has evolved significantly since its inception in the mid-twentieth century. The technology has transitioned from rule-based systems to advanced machine learning algorithms capable of self-improvement. Advancements in models such as transformers have facilitated a recent surge in AI adoption. These models have become instrumental in natural language processing tasks. For instance, Google's BERT (Bidirectional Encoder Representations from Transformers) has greatly enhanced search algorithms. Transformers are deep learning models that process sequential data; BERT is used for language understanding in search engines; GPT powers generative tasks like customer query handling. Even more relevantly, OpenAI GPT models have been employed in various customer service applications [1, 2]. These technological innovations allow businesses to optimize operations, scale services, and customize experiences. As AI continues to mature, its potential extends into various aspects of business, including the critical domain of customer loyalty [3–5]. Companies are increasingly leveraging AI-driven analytics and engagement tools to understand consumer behavior better, thus opening new avenues for fostering customer loyalty and enhancing long-term relationships [6]. However, prior literature has not quantitatively synthesized the extent to which AI influences customer loyalty in e-commerce, nor accounted for variation in AI application types.

Customer loyalty refers to the long-term relationship between a brand and its customers, characterized by repeat

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business and a propensity to choose one brand over its competitors. The importance of this concept cannot be overstated, especially in e-commerce [7, 8]. It has been established that retaining existing customers is generally more cost-effective than acquiring new ones. Traditional strategies to enhance customer loyalty have included loyalty programs, personalized marketing, and customer service initiatives. However, these methods often suffer from inefficiencies such as inaccurate targeting, limited scalability, and high operational costs [4, 9, 10]. Artificial intelligence solves these shortcomings by utilizing data-driven algorithms for personalized recommendations, automating customer service through chatbots, and enabling predictive analytics for customer behavior [6, 11]. By addressing the limitations of traditional strategies, AI provides a more efficient and effective approach to cultivating customer loyalty. Unlike traditional loyalty programs, AI enables real-time personalization, continuous learning, and automation, thus offering scalable and context-aware engagement. Consequently, there has been a burgeoning interest within the academic community to explore the transformative impact of AI on customer loyalty, underlining its significance in contemporary business and marketing research [12]. Table 1 shows the different classes of variables involved in this study.

The preceding discussions have underscored Artificial Intelligence's and customer loyalty's burgeoning significance in the evolving e-commerce landscape. The converging trajectories of AI and customer loyalty present an intriguing scope for inquiry within the e-commerce space. The sector is unique because it relies on technological innovations and customer engagement. Therefore, this paper aims to investigate the role of Artificial Intelligence in influencing customer loyalty within the e-commerce industry. Building on this foundational background, this study narrows its focus to the intersection of AI and loyalty within the e-commerce landscape. Specifically, the objectives of the study are threefold:

1. to determine the extent of AI's application in e-commerce, probing into how it is being utilized for various functions from marketing to customer service.
2. to ascertain the dynamics of customer loyalty in the e-commerce domain, examining how traditional loyalty-building strategies are being augmented or replaced, and
3. to establish the empirical relationship between AI and customer loyalty in e-commerce, seeking to understand how AI-driven tools and strategies affect customer retention and engagement.

In fulfilling the research objectives, the paper is structured into six sections, namely introduction, theoretical background, methodology, results, discussion, and conclusions and recommendations.

2 Theoretical background

The Expectation-Confirmation Theory (ECT), developed by Oliver in 1980 [13], underpinned the study. This theory is a valuable framework for understanding how consumers form satisfaction judgments post-purchase by comparing their initial expectations against the perceived performance of the product or service they have consumed [14]. ECT delineates key constructs such as pre-purchase expectations, perceived performance, confirmation or disconfirmation, and resultant satisfaction or dissatisfaction, providing an articulate model to investigate consumer responses [13, 15]. The theory's emphasis on post-purchase behavior and satisfaction makes it especially relevant for exploring the role of artificial intelligence in shaping customer loyalty within the e-commerce space. One of the key principles of the Expectation-Confirmation Theory is acknowledging pre-purchase expectations. Before engaging in a transaction, consumers develop specific anticipations regarding how a product or service will perform. Various factors shape these expectations, including prior experiences with comparable goods or services, targeted marketing campaigns, and recommendations or reviews from other customers [13, 16, 17]. Another essential facet of the expectation-confirmation

Table 1 Applications in each class

Variable type	Variable name	Description
Independent variable	Artificial intelligence	A multidisciplinary field of computer science that aims to develop systems capable of performing tasks that would normally require human intelligence. These tasks include, but are not limited to, natural language understanding, decision-making, visual perception, and problem-solving
Dependent variable	Customer loyalty	The ongoing preference and consistent patronage that consumers show towards a particular brand, product, or service over an extended period of time

theory is the concept of perceived performance. Following the purchase and utilization of a product or service, consumers evaluate its performance based on various criteria, such as quality, effectiveness, and overall value [3, 18].

Two pivotal constructs in the Expectation-Confirmation Theory are confirmation/disconfirmation and satisfaction/dissatisfaction. After consumers evaluate the perceived performance of a product or service, they experience either confirmation or disconfirmation based on the degree to which their pre-purchase expectations align with their post-purchase evaluations [19, 20]. Confirming or disconfirming expectations subsequently leads to either satisfaction or dissatisfaction. Specifically, confirmation occurs when performance meets or exceeds initial expectations, resulting in customer satisfaction. Conversely, disconfirmation emerges when performance falls short of expectations, culminating in dissatisfaction. For instance, an AI chatbot that resolves customer complaints accurately confirms expectations, whereas an unhelpful bot leads to disconfirmation and dissatisfaction [11]. The final stage in the Expectation-Confirmation Theory centers on post-purchase behavior, which is subject to the consumer's level of satisfaction or dissatisfaction [13, 21]. Satisfied customers are likelier to exhibit loyalty, repeat purchases, and advocate for the product or service through positive word-of-mouth. On the other hand, dissatisfied customers may switch to competitors and disseminate negative reviews. This behavior is key in the business context, particularly in e-commerce. In this industry, AI significantly bolsters or erodes customer loyalty based on their post-purchase experiences [22, 23].

The concept of attribution also plays a role in expectation-confirmation theory, shedding light on how consumers interpret the reasons behind disconfirmation [24]. When expectations are unmet, consumers seek to identify causes, which can be external factors like misleading advertising or internal factors like personal preference. These attributions further nuance their level of satisfaction or dissatisfaction, potentially affecting their loyalty and future interactions with the business. In the e-commerce landscape, AI-driven analytics could help businesses understand these attribution patterns. As a result, they offer targeted solutions to enhance customer satisfaction and loyalty [1, 25]. Alternative models like the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) focus on adoption behavior but fall short in explaining post-adoption satisfaction—making ECT more suitable for studying loyalty outcomes.

3 Methodology

3.1 Literature search

The literature search was extensive and detailed as shown in Fig. 1. A multi-database strategy was employed for the comprehensive literature search, targeting MDPI, IEEE Xplore, and ABI/INFORM as primary sources of scholarly articles. The most fruitful repository was MDPI, renowned for its extensive collection of open-access journals across various scientific disciplines, including business and technology. A combination of Boolean operators and carefully chosen keyword strings—focusing on terms like "artificial intelligence," "customer loyalty," and "e-commerce"—were employed in MDPI to optimize search outcomes. IEEE Xplore provided valuable insights into the technical aspects of AI applications, while ABI/INFORM enriched the study by offering a business-oriented perspective on customer loyalty strategies. The diversity of these databases ensured a multi-faceted approach to identifying relevant studies, thereby capturing a balanced view of the interdisciplinary nature of the research question at hand.

4 Keyword planning

In constructing the keyword planning strategy, meticulous attention was devoted to balancing specificity and breadth, given the interdisciplinary nature of the topic—AI and customer loyalty in e-commerce. Terms related to artificial intelligence were judiciously selected to capture its diverse facets; these included not just the general "artificial intelligence" but also more specialized

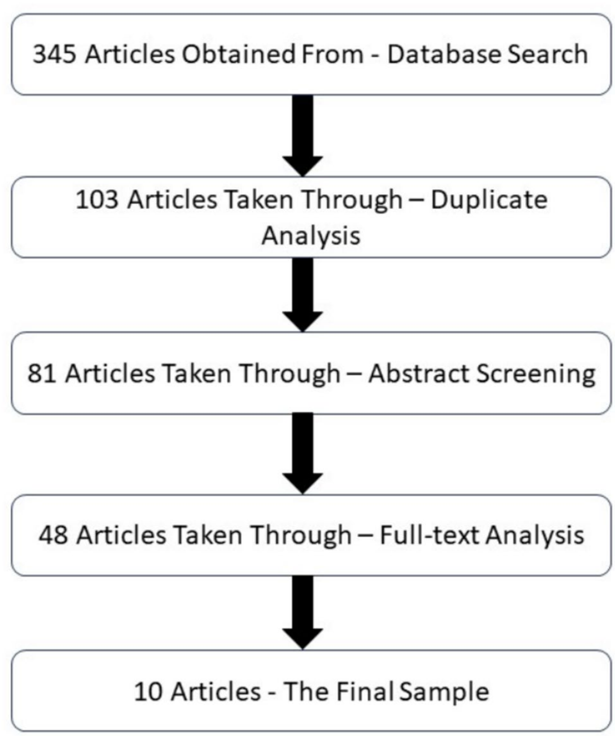

Fig. 1 Study filtering flowchart

terminologies such as "machine learning" and "natural language processing," which represent subsets of AI with unique applications in customer interaction and data analysis. Simultaneously, keywords encapsulating customer loyalty were chosen to reflect its multi-dimensional attributes. It led to the inclusion of terms like "customer retention," indicative of long-term loyalty; "customer satisfaction," which often serves as a precursor to loyalty; and "net promoter score," a metric directly correlating with customer advocacy. This layered approach in keyword planning ensured that the search would yield studies offering a nuanced view of the mechanisms through which AI influences customer loyalty. The end goal was to maximize search outcomes by covering a broad intellectual territory while minimizing the inclusion of irrelevant studies, thereby creating a fertile ground for a rich analysis.

4.1 Inclusion and exclusion criteria

A set of predetermined criteria was applied to screen potential articles to ensure methodological rigor and relevance to the study. Inclusion criteria were: (1) Studies must be quantitative, offering empirical evidence and statistical analyses. (2) Only articles published from 2020 onward were considered to ensure the research incorporates the most recent advancements in AI technology and loyalty metrics. (3) The type of AI application used in the study must be clearly defined, whether it involves machine learning algorithms, natural language processing, or other relevant AI technologies. (4) Loyalty metrics should be explicitly stated and could include variables like customer retention rates, customer satisfaction scores, or net promoter scores. (5) The sample size for each study must be provided, with a preference for larger samples that offer more robust statistical power. Studies not meeting these criteria were promptly excluded.

The researcher utilized a comprehensive search approach to identify relevant articles for the meta-analysis, initially extracting 345 articles from the above mentioned selected databases. This initial pool underwent a rigorous duplicate analysis, narrowing the selection down to 103 unique articles. Further refinement occurred during abstract screening, which led to the exclusion of 22 more articles, leaving 81 for full-text analysis. After a comprehensive full-text analysis, only 10 articles met the inclusion criteria and were selected for the final sample as shown in Fig. 1. Only studies that met all criteria—including relevance, statistical completeness, clear AI definition, and methodological transparency—were retained. High-impact studies without quantifiable metrics were excluded.

5 Reference checking

Reference checking played an indispensable role in fortifying the thorough search process. After identifying pertinent articles through initial database searches on MDPI, IEEE Xplore, and ABI/INFORM, we examined the references cited in these articles. This backward search was performed to uncover additional studies that may have escaped our initial search due to terminology or database limitations. It was particularly useful for identifying seminal papers and works that have been extensively cited but did not appear in our initial queries. Such a strategy enriched the diversity of perspectives in our study. Furthermore, it provided a more detailed understanding of the relationship between artificial intelligence and customer loyalty.

5.1 Expert consultation

In our study, expert consultation served as a supplementary yet crucial step in the research process. We sought guidance from academic advisors and professionals specializing in artificial intelligence, customer loyalty, and e-commerce. These consultations often yielded recommendations for seminal works and key authors that we may not have encountered through database searches alone. As a result, we enriched our study's scope and depth, ensuring a more robust and comprehensive analysis of the relationship between AI and customer loyalty.

5.2 Documentation of search strategy

Rigorous documentation has been a cornerstone of our methodology. We have maintained a detailed record of our search strategy, the databases consulted, and the number of articles found and subsequently evaluated. This practice serves dual purposes: it aids our internal organization and ensures replicability while fulfilling the transparency requirements commonly expected in scholarly publications. Such rigorous documentation lends credibility to our research process and facilitates potential future updates. Other researchers could also apply similar parameters used in this study to reproduce the results we obtained in this investigation. The reproducibility is possible because of the explicit description of the methodological procedures undertaken in this study.

5.3 Coding

The coding process for the selected studies was a meticulously structured endeavor to capture the key variables and metrics relevant to the research questions. Each study was coded according to a predetermined set of descriptive and statistical items. Descriptive items included metadata such as the author, publication year, source, and contextual information like the type of AI application used and the loyalty metrics assessed. Statistical items encompassed sample size and relevant correlation coefficients or other quantifiable metrics that could contribute to meta-analysis. Two research assistants trained in the study's objectives and methodology performed this coding task independently. The researcher took this step to ensure reliability and mitigate potential bias. Following the independent coding, their outputs were cross-checked for consistency, and any discrepancies were resolved through discussion or consultation with a senior researcher. Special attention was paid to statistical items like Pearson correlation coefficients, as shown in Table 2, as these were instrumental in calculating effect sizes for the meta-analysis.

5.4 Computing effect sizes

Computing effect sizes is a crucial step in meta-analysis as it offers a standardized measure of the magnitude of a phenomenon, allowing for comparison across different studies. This research used the statistical software Stata 15 for data synthesis and analysis, focusing on employing the random-effects model due to the inherent heterogeneity in study designs and regions. Effect sizes were primarily calculated using Fisher's Z transformation, a common method for converting correlation coefficients to a scale that permits more straightforward meta-analytical evaluations. Fisher's Z was selected for its ability to normalize correlation coefficients across varying sample sizes, allowing more reliable aggregation. The formula for Fisher's Z transformation [26, 30] is as follows:

$$Fisher's\ Z = 0.5 \times ln\left(\frac{1+r_i}{1-r_i}\right)$$

Table 2 Summary of coding information of identified studies

Study	Journal	n	Effect
[6]	*Frontiers in Psychology*	332	r
[26]	*SSBM*	257	r
[20]	*Journal of Data Acquisition and Processing*	593	r
[22]	*UMEA*	30	r
[27]	*Federal University of Paraíba*	85	r
[17]	*EQM ResearchBerg*	218	r
[12]	*Journal of Retailing and Consumer Services*	337	r
[28]	*King AbdulAziz University, KSA*	3290	r
[1]	*Proceedings of the First ASEAN Business, Environment, and Technology Symposium*	343	r
[29]	*Journal of System and Management Sciences*	381	r

where r_i is the reported correlation coefficient from an individual study. The weighted mean effect size, denoted as z_+, was calculated using the following equation [27]:

$$z_+ = \frac{\Sigma_{i=1}^{N}\left(w_i \times z_i\right)}{\Sigma_{i=1}^{N} w_i}$$

Here w_i is the weight value for each study and z_i is the Fisher's Z value for the corresponding study. To assess the heterogeneity across the included studies, Q-statistics and I^2-values were used [29].

We obtain Q through this equation.

$$Q = \sum_{i=1}^{N} w_i(z_{i-}z_+)$$

where w_i = the weight value of the i_{th} study.

Significance heterogeneity was deemed to exist if $p < 0.01$ and I^2 was equal to or greater than 80%. The I-squared statistic I^2 is a metric employed in meta-analysis to quantify the degree of heterogeneity among the studies included [28]. Heterogeneity in this context refers to the variability in study outcomes between the studies. The equation for I^2 [26] is shown below.

$$I^2 = \left(\frac{Q-N+1}{Q}\right) \times 100$$

In this equation, Q is the heterogeneity statistic, and N is the number of studies. These computations aid the study in providing a robust quantitative synthesis of the literature on the role of artificial intelligence in customer loyalty.

As a result, it offers clearer insights into this important field. The equation for finding the lower and upper bounds [29] is shown below.

$$bounds = r_z \pm 1.96 \times s.d$$

where s.d = standard deviation.

In determining the publication bias, the study used the fail-safe N and its critical value k. The Fail-safe N (Nfs), often referred to as the "file drawer problem," is a statistical measure used in meta-analyses to assess the robustness of the findings. Essentially, it quantifies how many unpublished or "filed away" studies with null results would be needed to invalidate the significant effect observed in the meta-analysis [26]. A larger Nfs value implies that the meta-analysis results are more robust and less likely to be influenced by publication bias. If the Nfs is large compared to the number of studies included in the meta-analysis, one can be more confident that the significant findings are not merely artifacts of publication bias [27]. Below are the equations for computing the two metrics [28].

Table 3 Descriptive analysis

Variable	k	r (min)	r (max)	N
AI and loyalty	10	0.497	0.909	6296

Table 4 Publication bias risk analysis

Nfs	Critical Nfs	Bias
67.751	60	Low

$$Fail - safeN(N_{fs.05}) = \left(\frac{\sum_z}{1.645}\right)^2 - N$$

Critical value = 5 × k + 10. Where N = number of studies included the meta-analysis, k = the number of studies in the meta-analysis and z = the converted z-statistic.

6 Results

6.1 Data description

We analyzed ten papers, encapsulating a sample size of 6296 participants as shown in Table 3. The Pearson correlation coefficients (r) for these studies ranged from a minimum of 0.497 to a maximum of 0.909. The values show that the two variables had a moderate to high and positive relationship. The range of correlation coefficients suggests variability in how AI impacts customer loyalty metrics. It is also an indication that while AI generally has a positive influence, the strength of this influence varies.

6.2 Publication bias risk

Table 4 offers a focused view of publication bias, providing key metrics such as the Fail-safe Number (Nfs), its critical value, and an overall assessment of bias risk for the meta-analysis. The table indicates an Nfs value of 67.751, surpassing the critical threshold of 60. In terms of assessing the robustness of meta-analytical findings, an Nfs value exceeding the critical value generally signals that a large number of null studies would be needed to nullify the observed effect sizes, thus lending credibility to the meta-analysis results. In this context, the risk of bias is assessed as “Low.” This strengthens confidence that findings are not skewed by selective publication or suppressed null results. The data underscores the general robustness of the findings across the studies included in the meta-analysis, making them less susceptible to the influence of publication bias.

6.3 Effect of AI on customer loyalty

The findings pertaining to the impact of AI on consumer loyalty are synthesized in Tables 5 and 6. In terms of publication bias, Table 6 reveals a low risk, signaled by an Nfs value of 67.75 that exceeds the critical Nfs of 60. This suggests that the studies included in the meta-analysis are resilient to the file-drawer problem, thereby fortifying the trustworthiness of the results.

Table 6 also amalgamates outcomes from 10 studies, highlighting a substantial positive correlation (r = 0.761)

Table 5 Study summery

Study	Year	AI application	Loyalty metrics	Sample size	r	Fisher’s Z	Weight
[6]	2022	General	Customer engagement	375	0.57	0.65	372
[26]	2022	Chatbots	Customer retention	300	0.77	1.02	297
[20]	2023	General	General	636	0.88	1.39	633
[22]	2023	Chatbots	General	73	0.60	0.69	70
[27]	2022	Recommender systems	General	128	0.86	1.29	125
[17]	2020	Chatbots, recommender systems, NLP	General	261	0.80	1.10	258
[12]	2020	Chatbots	Customer engagement	380	0.84	1.21	377
[28]	2021	Classifiers	Customer retention	3333	0.91	1.52	3330
[1]	2020	General	General	386	0.88	1.38	383
[29]	2023	Chatbots	General	424	0.50	0.55	421

Table 6 Aggregated summary

Variable	k	*df*	r	CI	Q	p-value	I^2 (%)	z_+	N	Nfs	Crit. Nfs	p. bias risk
Loyalty metrics	10	9	0.761	[1.29, 1.34]	634.8252938	P < 0.001	69.01	1.31	6296	67.75	60	Low

between AI interventions and customer loyalty. This level of correlation suggests that organizations using AI can expect a meaningful uplift in customer engagement and retention outcomes. The Z-score of 1.31 and a p-value less than 0.001 effectively reject the null hypothesis, implying a non-zero effect size. This demonstrates a robust and statistically significant relationship between AI applications and consumer loyalty metrics.

Nevertheless, it's crucial to address the noticeable heterogeneity across the studies, indicated by a Q statistic of 634.825 and an I^2 value of 69.01%. Such heterogeneity often signals unaccounted moderating variables, which could vary from types of AI applications to customer demographics, demanding further investigation [22]. The observed heterogeneity likely arises from varied AI types, measurement instruments, and regional settings—suggesting the need for further segmentation analysis in future research.

The robustness of these findings is further underlined by a substantial total sample size (N = 6296). Thus, when combined with the low risk of publication bias, the meta-analysis robustly affirms the positive influence of AI on customer loyalty in the realm of e-commerce. The results, although strong, contain heterogeneity that requires further exploration.

7 Discussion

The results of this meta-analysis indicate that artificial intelligence plays a substantial role in augmenting customer loyalty within the ecommerce industry. This view is consistent with [31] who demonstrates that the association between the two variables possesses distinct characteristics, as it can be influenced by confounding factors such as managerial competence and strategic decision-making. However, it is important to note that all the studies incorporated in the analysis reached a consensus. They all suggested that an augmentation in the utilization of artificial intelligence is expected to favor customer loyalty while keeping other variables constant [6, 12, 17, 32]. The significance of this relationship is notable due to the remarkable adoption of the technology within the realm of electronic commerce in recent years.

The analysis conducted in this study also indicates that the relationship is not straightforward, as evidenced by the observed heterogeneity. These findings align with emerging meta-analyses in marketing tech domains that report moderate to high effects of digital tools on loyalty. The statistical data should be interpreted within the context of the underlying dynamics present in the study. While certain scholars have conducted comprehensive investigations on artificial intelligence, others have focused their attention on specific facets of this technology, such as natural language processing [33], chatbots [22], classifiers [17], and recommender systems [32]. These variations can potentially impact the strength of cause-effect relationships. The observation that all studies consistently reported a positive correlation between the two variables indicates that the dynamics solely influence the magnitude of the relationship rather than altering its direction.

The dynamics in how the studies conceptualize AI's role in e-commerce warrant closer scrutiny. Different facets of AI—be it in a general sense, chatbots, recommender systems, or classifiers—have been considered across the various studies [16]. Such divergence in conceptualization could partly account for the observed heterogeneity in the meta-analysis. For instance, recommender systems might have different implications for customer retention than chatbots due to their personalized suggestions. Similarly, using classifiers for customer segmentation could affect customer loyalty in ways that generic AI applications may not [34]. In our analysis, recommender systems and chatbots emerged most frequently, with recommender systems often yielding higher loyalty correlations. Despite these conceptual variances, all studies consistently report a positive correlation between AI and loyalty metrics, albeit to different extents. It suggests that the multi-faceted nature of AI applications could influence the magnitude of its impact on customer loyalty but not change the direction of this relationship.

The studies examined in this paper employed varying measurement paradigms to assess the customer loyalty variable. Most individuals regarded it holistically, while a subset employed specific metrics for evaluation. For instance, one study by [18] examined the metric of customer retention rates, whereas another study [6, 12] assessed it based on customer engagement metrics. Similar to the variations in conceptualizing artificial intelligence, these dynamics can also impact the observed nature of relationships, owing to the disparities in the methodologies scholars employ to measure AI. Notably, most studies have primarily focused on customer loyalty in a general sense, neglecting to recognize its distinct types and metrics.

The inconsistency in conceptualizing customer loyalty across the analyzed studies introduces additional complexity to the meta-analysis. While some studies focus on specific aspects like customer retention or engagement, others approach loyalty more broadly. This heterogeneous treatment of the loyalty variable could significantly contribute to the statistical heterogeneity observed in the study's outcomes. For example, customer engagement might correlate more strongly with AI applications like chatbots, which aim to keep the customer involved and informed [22, 31]. On the other hand, customer retention, a longer-term metric, might be more closely related to recommender systems that personalize the customer's experience over time. The varying approaches to measuring customer loyalty can dilute or intensify the observed effects of AI applications on this metric.

8 Conclusion, limitation and recommendation

8.1 Conclusion

In summary, this meta-analysis highlights the substantial influence of artificial intelligence implementations on customer loyalty in the e-commerce industry. The collective effect size, although influenced by some level of variability, indicates a moderate to strong positive association between the utilization of artificial intelligence (AI) and metrics related to customer loyalty. The assertion is supported by a significant Q-statistic and considerable heterogeneity (I2), indicating the complex influence of various AI technologies and diverse conceptualizations of customer loyalty. The relationship between loyalty and AI technologies consistently exhibits a positive direction across various studies despite variations in the metrics employed to evaluate loyalty and the specific AI technologies under investigation. It is crucial to acknowledge that although the outcome strongly supports a positive influence, the variability indicates that not all artificial intelligence (AI) applications are equally successful in fostering customer loyalty. The variations in the application of artificial intelligence, which includes chatbots and classifiers, as well as differences in the conceptualization of loyalty metrics, can be identified as contributing factors to this phenomenon. Recognizing that different customer segments respond uniquely to AI interventions is vital for maximizing loyalty outcomes. The findings and discussions are consistent with the expectation-confirmation theory underpinning the study. The aforementioned comprehensive comprehension underscores the imperative of adopting a more detailed methodology in forthcoming research endeavors about artificial intelligence implementations and measures of customer loyalty.

8.2 Limitation

A noteworthy constraint of this meta-analysis pertains to the limited number of studies incorporated, potentially impeding the extent to which the findings can be applied to a broader population. The small number of studies limits the generalizability of results and prevents rigorous subgroup analyses. With more studies, confidence intervals would narrow, and moderators like industry or geography could be tested. Expanding the research scope would enhance statistical robustness and yield a more comprehensive understanding of the contemporary academic terrain. The restricted sample size also prevents the opportunity to conduct significant subgroup analyses to investigate the intricacies among various categories of AI applications or customer loyalty metrics. The lack of detailed information limits the capacity to provide precise and customized suggestions that cater to the intricacies of various artificial intelligence (AI) applications in electronic commerce. Moreover, the analysed studies exhibit a range of methodologies and varying degrees of quality, thereby introducing an additional level of intricacy in the analysis and understanding of the findings. It is important to recognize that the variability in research methodologies, artificial intelligence implementations, and measures of customer loyalty may have influenced the variability in observed effect sizes, consequently impacting the reliability of the findings.

8.3 Recommendation

Our research demonstrates that artificial intelligence technology implementation directly affects customer loyalty in online businesses. e-commerce companies should use AI systems designed to encourage loyalty among customers. These technologies use recommender systems to deliver personalized product choices and they employ predictive analytics to detect loss possibilities and perfect sales guard strategies. Chatbots using large language models can help manage standard customer questions more swiftly which boosts user confidence and contentment in the service experience.

Businesses need to create specific steps to put these technologies into practice. They should start by conducting a digital system review to check AI readiness. Companies should begin testing basic AI systems including chatbots in distinct sections including customer FAQ and shipping updates. Their performance results will show them how to develop recommendation engines that automatically customize user pathways as people interact. A combined team of data analysts marketing staff and IT professionals needs to set up taskforces to help integrate AI solutions into business operations.

Businesses should look for AI talent both in technical roles and employee segments that best support their loyalty aims. To create emotional loyalty, firms should hire staff with sentiment analysis and NLP expertise but for behavioral loyalty they need predictive modeling and machine learning professionals. Organizations need to teach their current employees basic AI knowledge to create a workplace that uses data to make decisions. Firms must create AI research centers within their organization or team up with educational institutions to stay ahead of technology updates because AI technology develops very quickly. Firms staying invested in research enables them to approach new AI technology developments quickly and with effective planning.

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Data availability The data presented in this study are available on request from the corresponding author.

Declarations

Conflict of interest The author declares no conflicts of interest.

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